

# A Generalized Approach to Real-Time Pattern Recognition in Sensed Data

Ayanna Howard and Curtis Padgett  
Jet Propulsion Laboratory, California Institute of Technology  
4800 Oak Grove Drive, Pasadena, CA 91109-8099

## Abstract

Many applications that focus on target detection in an image scene develop algorithms specific to the task at hand. These algorithms tend to be dependent on the type of input data used in the application and thus generally fail when transplanted to other detection spaces. We wish to address this data dependency issue and develop a novel technique which autonomously detects, in real time, all target objects embedded in an image scene irrespective of the imagery representation. We accomplish this task using a hierarchical approach in which we use an optimal set of linear filters to reduce the data dimensionality of an image scene and then spatially locate objects in the scene with a neural network classifier. We prove the generality of this approach by applying it to two distinctly separate applications. In the first application, we use our algorithm to detect a specified set of targets for an Automatic Target Recognition (ATR) task. The data for this application is retrieved from two-dimensional camera imagery. In the second task, we address the problem of sub-pixel target detection in a hyperspectral image scene. This data set is represented by hyperspectral pixel bands in which target objects occupy a portion of a hyperspectral pixel. A summarized description of our algorithm is given in the following section.

## 1 Technique

Given a set of target objects  $T$ , the goal of the algorithm is to detect, in real time, any target  $t \in T$  present in an image scene  $I$ . We define  $i \in I$  as the smallest classifiable subset of  $I$  which fully encompasses a target object. Given this data set, a knowledge base is first developed through the following preprocessing steps:

- Data Dimensionality Reduction
  - Identify a set of image cluster prototypes used to segment the image scene.
  - Derive a set of linear filters used to optimally separate targets embedded in an image scene from other typical images.
- Neural Network Classification
  - Train a set of expert neural network classifiers that receive as input the image data projected onto a linear filter set and respond with 1 when targets are embedded in the scene and -1 otherwise.

### 1.1 Data Dimensionality Reduction

In a typical detection application, the data extracted from an image scene will have a multitude of data dimensions. Our first task is to reduce this data dimensionality in order to effectively manage the image space. This task is accomplished with two separate procedures: clustering and filtering.

#### 1.1.1 Filter Sets

The filtering step involves an orthogonal sub-space projection of the image subset  $i$ . It is used to optimally linearly separate the embedded target images from those images not containing targets. This is a standard technique used to reduce the dimensionality of an image set while preserving as much of the signal as possible. The filters associated with a given prototype are derived from the distribution of an image scene (*noise*) and the distribution of potential targets embedded in that image (*signal*). This can be optimally separated to maximize the signal to noise ratio between the two groups using directed principal components analysis (DPCA).

To characterize the distribution for the image scene, the covariance matrix,  $R_i$ , is found for image subsets which do not contain targets. We characterize the embedded target image distribution by its covariance matrix,  $S_i$ . We

are interested in finding a set of orthogonal basis vectors  $W_i$ , that maximizes the expected signal to noise ratio of these two distributions defined by their respective image sets. The generalized eigenvector solution:

$$S_i W_i = \lambda R_i W_i \quad (1)$$

accomplishes this. The set of filters defined by  $W_i$  is the directed components used in our algorithm to steer the eigenvector solution away from dimensions of high noise variance in a linearly optimal fashion.

### 1.1.2 Clustering

To effectively simplify the distribution of data classified by an expert neural network, we partition the incoming image data set into a number of predetermined groups by using the prototypes  $P_i$  of a clustering algorithm. Depending on the dimensionality of the data, this step can be accomplished either before, or after, the filtering step. The clustering algorithm is run on previously acquired data that reflects the distribution of the scene being analyzed. This data will either consist of raw sensor data or of data projected on the linear filter set. In either case, the clustering algorithm will not be dependant on the type of imagery representation.

The clustering algorithm employed is a modified version of a standard clustering technique outlined in Duda and Hart [3]. The standard algorithm uses a standard least squares criterion to minimize the distance between each of  $n$  randomly selected groups. The criterion minimized by the standard clustering algorithm is:

$$cost = \sum_i \sum_j \| p_j - P_i \| \quad (2)$$

where  $i$  is one of  $n$  clusters,  $j$  is one of  $m$  image subsets, and  $p_j$  is the actual data pattern used to represent the image subset. The clustering algorithm iterates through each data pattern and determines if moving the pattern to another group reduces the overall cost. If it does, the pattern is moved to the other group and the associated averages of each prototype cluster are recalculated. This continues until the moving of patterns no longer reduces the overall cost. The resultant cluster prototypes are then employed by our algorithm to segment the image scene.

The clustering algorithm, as described, is independent of the detection problem. It does not take into account any information that we might have concerning the target set. This apriori information enables us to perform such operations as biasing the clustering algorithm to have narrower distributions for data patterns that resemble the target set and wider distributions for those patterns that contrast with them. In addition, we can bias the algorithm to reward the moving of patterns into clusters that contain like patterns and penalize for moving a pattern to those containin unlike patterns. This will allow the clustering algorithm to naturally link alike elements together. To utilize this target set information, we include a weighting term  $w_j$  into the criterion evaluation.

$$cost = \sum_i \sum_j w_j \| p_j - P_i \| \quad (3)$$

The weighting term is determined based on the clustering attributes desired. To change the distribution width, we let

$$w_j = \frac{1}{\sum_s p_j - t_s} \quad (4)$$

If we want to group alike patterns together, we let

$$w_j = 1 + \frac{nt_i}{np_i} \left(1 - \frac{nt_i}{np_i}\right) \quad (5)$$

where  $s$  is one of  $T$  targets,  $nt_i$  is the number of targets present in cluster  $i$ , and  $np_i$  is the total number of data patterns present in cluster  $i$ .

Once the clustering step is finished, we will have  $n$  cluster prototypes representing the image scene. These clustering and filtering procedures allows us to reduce the dimensionality of the data in order to effectively detect targets embedded in an image scene in real time. We now use this data to train a neural network for real-time target detection.

## 1.2 Classification

The classification step involves classifying each projected data pattern belonging to cluster  $i$  with a neural network. We will thus have  $n$  neural networks linked to  $n$  cluster prototypes. The networks are trained with data drawn from the two distributions: background data patterns  $R_i$  and embedded target patterns  $S_i$ . The expert network for class  $i$  is required to respond with 1 for elements drawn from  $S_i$  and -1 from those drawn from  $R_i$ . We use a simple feed forward network model employing sigmoidal hidden units trained with backpropagation to get the desired result. The output can then be thresholded to achieve the desired detection and false positive rate.

## 2 Implementation

Once the preprocessing steps are implemented, we can perform the task of real-time intelligent target detection which is independent of the data representation. We first perform the data dimensionality reduction step which gives us a data set consisting of the image set projected onto the set of linear filters. We then use the trained neural network classifier to evaluate whether or not the extracted data pattern contains a target  $t \in T$ . The neural network for each cluster group takes as input the projected values of an image subset and outputs a value. Values above a threshold are considered images with targets and those below are assigned to background. The effectiveness of the evaluation requires that the cluster prototypes generated and the image subsets used in training the classifier must be derived from scenery with roughly the same distributions as encountered in the operational test.

We evaluated the overall performance of the algorithm using two separately distinct image sets. In the first application (ATR), the background image scenes consist of over one million 40x40 camera image pixel blocks of which less than 5% were used in developing a set of training data. For the sub-pixel target detection application, we use two hyperspectral image scenes consisted of over 3/4 of a million 254 hyperspectral pixel bands of which less than 10% were used in developing a set of training data. Running our algorithm on these two sets of data give us a detection rate of 96% with a false positive rate of less than 0.03% for the ATR application. For the hyperspectral application, our algorithm was shown to have a rate of detection of over 99% with false positives less than  $10^{-4}$  on a set of targets mixed at 10%. These favorable detection rates show us that our algorithm can generalize, and is not dependent on the representation of the images.

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## References

- [1] C. Daniell, D. Kemsley, W. Lincoln, W. Tackett, and G. Baraghimian. Artificial neural networks for automatic target recognition. *Optical Engineering*, 31(12):2521–2530, 1992.
- [2] K. Diamantaras and S. Kung. *Principal Component Neural Networks: Theory and Applications*. John Wiley and Sons, New York, 1996.
- [3] H. Duda and M. Hart. *Pattern Classification and Scene Analysis*. John Wiley and Sons, New York, 1973.
- [4] J. Harsanyi and C. Chang. Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection approach. *IEEE Transaction on Geoscience and Remote Sensing*, 32:779–785, 1994.
- [5] S. Haykin. *Neural Networks: A Comprehensive Foundation*. Macmillan College Publishing Company, New York, 1994.
- [6] A. Howard, C. Padgett, and C. Liebe. A multi-stage neural network for automatic target detection. In *1998 IEEE World Congress on Computational Intelligence*, Anchorage, AL, 1998.